

A universal assortativity measure for network analysis

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Characterizing the connectivity tendency of a network is a fundamental problem in network science. The traditional and well-known assortativity coefficient is calculated on a per-network basis, which is of little use to partial connection tendency of a network. This paper proposes a universal assortativity coefficient (UAC), which is based on the unambiguous definition of each individual edge's contribution to the global assortativity coefficient (GAC). It is able to reveal the connection tendency of microscopic, mesoscopic, macroscopic structures and any given part of a network. Applying UAC to real world networks, we find that, contrary to the popular expectation, most networks (notably the AS-level Internet topology) have markedly more assortative edges/nodes than dissortative ones despite their global dissortativity. Consequently, networks can be categorized along two dimensions—single global assortativity and local assortativity statistics. Detailed anatomy of the AS-level Internet topology further illustrates how UAC can be used to decipher the hidden patterns of connection tendencies on different scales.

PACS numbers: 89.75.Fb, 89.75.Hc, 89.20.Hh

I. INTRODUCTION

Network has become a useful and proliferative tool in a wide spectrum of research areas, ranging from traditional communication and transportation networks to more recently emerging networks as complex as online social networks and brain networks [1–15]. Assortativity coefficient is a basic metric that characterizes the connectivity tendency of a network, i.e., globally, whether nodes of similar (or dissimilar) degrees are more likely to be connected [16]. However, this metric is a macroscopic property, which becomes useless when microscale or mesoscale level analysis is required. In other words, one can not tell the exact intra-group or inter-group connection tendencies from the per-network assortativity coefficient.

Experimental studies have shown that various forms of groups are hidden in real networks. These groups can take the form of community, motif, clique, etc [19–21]. Multi-scale, especially mesoscale analysis is very important to understand the roles and dynamics of these groups [17, 18]. However, previous studies typically focus on the uncovering of these groups within a network, and treat isomorphic modular components to be identical. In other words, the component is solely studied as a subgraph extracted out of the whole network, totally neglecting the links connecting this subgraph to other parts of the graph. Obviously, this traditional method inevitably fails to capture the functional difference between isomorphic modular components. Indeed, functional roles or dynamics of a group can only be comprehensively understood when it is put in the global context. An im-

portant distinguishable property is whether the group under consideration is assortatively mixed or dissortatively mixed within its local surroundings, which can have quite different influence on the dynamics, e.g., information diffusion/disease spreading [22], resilience against attacks [23]. Fig. 1 gives an illustrative example. In this figure, two triangles A and B are located in different surroundings. Triangle A is surrounded by high-degree nodes, i.e., dissortatively mixed with the outside world, whereas triangle B is surrounded by low-degree nodes, i.e., assortatively mixed with the outside world. This causes A and B to behave quite differently in the process of information or disease diffusion. In this simple example, suppose SIR model is used to model a disease spreading process and the infectious probability p is set to 0.5. If A serves as the source of the spreading process, the expected number of infected nodes accounts for about 23% of all the nodes, in contrast, if B serves as the source, then only less than 4% of the nodes are expected to be infected. This drastic discrepancy apparently comes from the difference in the connectivity tendency between the two triangles and their respective outside worlds.

Hence, in order to exactly analyze and explore network structure, which is beneficial to better understand the dynamics of complex systems, it is of critical significance to perform intra-group or inter-group connection tendency measurement in the global context. In this paper, we propose a universal assortativity coefficient that is based on the unambiguous definition of each individual edge's contribution to the global assortativity coefficient. This metric allows assortativity analysis on any part of a network and reveals some hidden network connectivity patterns.

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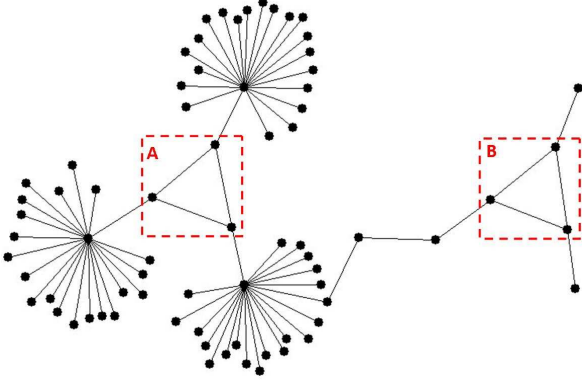


FIG. 1. An illustrative example showing how local connectivity pattern differentiate two isomorphic components (ie. A and B). Different local connectivity patterns always have different effects on dynamics, such as disease spreading.

II. UNIVERSAL ASSORTATIVITY COEFFICIENT

In order to measure the assortativity of the network on different scales, we proposed a uniform metric called universal assortativity coefficient that measures the assortativity of any subset of connections. Simply put, it is the summation of each individual edge's contribution to the global assortativity coefficient. Hence, we begin with our definition of each individual edge's contribution to the global assortativity coefficient.

Before the formal definition, it is necessary to review some related concepts discussed by Newman [16]. For simplicity, all the concepts we discuss are based on undirected networks. With minor or moderate adjustments, these concepts can also be applied to directed networks. Degree distribution $p(k)$ refers to the probability that a randomly chosen node is of degree k . The remaining degree distribution $q(k)$ refers to the probability that following a randomly chosen edge, the remaining degree of the reached node is k . Here, the remaining degree is the number of edges leaving this node other than the one we arrived along. This number is one less than the total degree of this node. The normalized distribution $q(k)$ of the remaining degree is:

$$q(k) = \frac{(k+1)p(k+1)}{\sum_j jp_j} \quad (1)$$

Joint probability distribution of the remaining degrees of two endpoints at either end of a randomly chosen edge e_{ij} is the probability that the remaining degrees of two endpoints of a randomly chosen edge are i and j .

Following these definitions, the assortativity coefficient r is defined as:

$$r = \frac{1}{\sigma_q^2} [\sum_{jk} jk(e_{jk} - q(j)q(k))] \quad (2)$$

where σ_q is the standard deviation of the remaining degree distribution $q(k)$.

For uncorrelated network, $r=0$; when the network is assortatively mixed, i.e., nodes of similar degrees are more likely to get connected, r is positive; when the network is dissortatively mixed, i.e., nodes of dissimilar degrees tend to connect to each other, r is negative.

Now considering each individual edge's contribution to the network assortativity coefficient r . Denote $U_q = \sum_j jq(j)$ to be the expected value of remaining degree, then r can be rewritten as:

$$\begin{aligned} r &= \frac{1}{\sigma_q^2} [\sum_{jk} jk(e_{jk} - q(j)q(k))] \\ &= \frac{\sigma_{jk}jk e_{jk} - U_q^2}{\sigma_q^2} \\ &= \frac{\sigma_{jk}jk e_{jk} - \sum_j jq(j) - \sum_k kq(k) + U_q^2}{\sigma_q^2} \\ &= \frac{\sigma_{jk}jk e_{jk} - \sum_j j \sum_k k e_{jk} - \sum_k k \sum_j j e_{jk} + U_q^2}{\sigma_q^2} \\ &= \frac{\sum_{jk} jk e_{jk} - \sum_j \sum_k (j+k) e_{jk} + U_q^2}{\sigma_q^2} \\ &= \frac{\sum_{jk} (j - U_q)(k - U_q) e_{jk}}{\sigma_q^2} \\ &= \frac{E(J - U_q)(K - U_q)}{\sigma_q^2} \end{aligned}$$

where J and K are variables of the remaining degree, which have the same expected value U_q . Following the above equation, we see that each edge's contribution to r is :

$$\rho_e = \frac{(j - U_q)(k - U_q)}{M \sigma_q^2} \quad (3)$$

where M is the number of edges, and j, k are the remaining degrees of the two endpoints of edge e . It is easy to see that $r = \sum_{i=1}^M \rho_e$.

When the network is completely homogeneous, i.e., all nodes have the same degree, then $\sigma_q = 0$. In this case ρ_e becomes undefinable. Since in this case, each edge has the same contribution to r , we define ρ_e to be $\frac{1}{M}$.

If $\rho_e > 0$, then e is called an assortative edge; otherwise if $\rho_e < 0$, it is called a dissortative edge. In this definition, if both the endpoints' remaining degrees are greater (or less) than the global expected remaining degree U_q , then the edge is assortative, and the more the two endpoints' remaining degrees deviate from U_q , more assortative the edge is. Otherwise, the edge is dissortative. In other words, the edge assortativeness is a scaled difference between the two endpoints' remaining degrees and the global expected remaining degree. The absolute value of the contribution $|\rho_e|$ is termed as the assortative/dissortative strength of the corresponding edge. We define S_{ae} to be the average strength of assortative edges,

and S_{de} to be the average strength of dissortative edges. The ratio of assortative edges is denoted by $P(\rho_e > 0)$.

Finally, the universal assortativity coefficient for a targeted edge set E_{target} is defined as:

$$\rho = \sum_{e \in E_{target}} \rho_e = \sum_{e \in E_{target}} \frac{(j - U_q)(k - U_q)}{M\sigma_q^2} \quad (4)$$

Based on this metric, it is easy to measure the assortativity on different scales. For example, to measure the connectivity tendency of a single node, denoted as ρ_v , simply set E_{target} to be the edges emanating from the node. If $\rho_v > 0$, then we call v to be an assortative node, otherwise if $\rho_v < 0$, we call v to be a dissortative node. To measure the connectivity tendency within a group, E_{target} is set to the edges within this group. If we set E_{target} to be the whole edge set E , then we arrive at the Newman's global assortativity coefficient [16]. In order to measure the connectivity tendency between groups, simply set E_{target} to be the edges between the groups. In this sense, this metric can be used to measure connection tendencies on different scales, thus, it deserves the name uniform assortativity coefficient (UAC).

Back to our example in Fig. 1, the global assortativity coefficient ρ is -0.804, indicating strong dissortativity. However, this global knowledge is of little use to understand the functional roles of local components, such as A and B . Based on UAC , we can quantitatively measure the connection tendency between A and the remaining graph, as well as between B and the remaining graph. It turns out that the inter-group assortative coefficient between A and the remaining graph is -0.033, whereas the inter-group assortative coefficient between B and the remaining graph is 0.025. As a consequence, although A and B are isomorphic when they are extracted out of the graph, their different connectivity tendencies to the other part of the graph result in drastic discrepancy in the disease spreading process. This example clearly tells us the significance of partial connection tendency for network analysis.

III. REAL NETWORK ANALYSIS

We apply the UAC analysis to various real-world networks. Table I reports r , $P(\rho_e > 0)$, S_{ae} , S_{de} and $P(\rho_v > 0)$ for different kinds of networks. These networks can be roughly categorized as five kinds: technical networks, biological networks, social networks, online social networks, and synthesized networks.

From this table, we see:

1. For a majority of real networks considered in this paper, e.g., AS, Router, Email-Enron, despite their impressive global dissortativity, we surprisingly find that the number of assortative edges/nodes exceeds dissortative edges/nodes. Whereas for the synthesized ER network, the number of assortative edges almost equals that of dissortative edges,

and their average strengths are indistinguishable as well. Hence, the network as a whole has no mixing pattern.

2. The global network assortativity is determined by both the ratio of assortative edges and the strength of these edges. For instance, in SCN, both the ratio of assortative edges and the average strength of assortative edges are greater than dissortative edges, hence it exhibits strong assortativeness as a whole. In comparison, though the number of assortative edges in the AS network also exceeds dissortative ones, the average strength of assortative edges is much weaker than dissortative ones. Hence, the dissortativity of this network comes from the relatively stronger strength of smaller number of dissortative edges. This is true for quite a number of other dissortative networks.
3. Here we reconfirm the fact that online social networks are dissortatively mixed, whereas real-world social networks are assortatively mixed [36]. We observe that the ratio of assortative edges in online social networks are comparatively lower than that of real-world social networks, although the total number of assortative edges still exceeds dissortative ones. However, the average strength of dissortative edges is greater than that of assortative edges in online social networks, in contrast, in real-world social networks, the situation is just the opposite. This reflects the fact that online social networks can to some extent eliminate social barrier between people of different social positions, making it is much easier for people at the bottom of society to setup links to people at the top of society.
4. According to global assortativity and local edge assortativity statistics, networks can be categorized to four kinds: globally assortative with leading number of assortative edges, globally assortative but with leading number of dissortative edges, globally dissortative with leading number of dissortative edges, globally dissortative but with leading number of assortative edges. Table II categorizes the networks along the two dimensions. Yet, it still remains an open question whether there is a real network that exhibits global assortativity but primarily consists of dissortative edges.

In the following, we use the AS-level Internet topology as an example to illustrate how the universal assortativity coefficient can be used to calculate the connectivity tendency of intra-group or inter-group connections. In the AS-level topology, a natural group partition of clear and explicit meaning is to partition the ASes according to their geographical regions. Today, five regional Internet registries (RIR) are managing the allocation and registration of Internet number resources (including AS numbers) within a particular region of the world. The five RIRs are: AfriNIC for Africa, ARIN for the United

TABLE I. Connection tendencies for different categories of networks.^a

Category	Name	r	$P(\rho_e > 0)$	S_{ae}	S_{de}	$P(\rho_v > 0)$
Technical Network	AS-2011-6 [24]	-0.184	60.4%	1.96×10^{-6}	8.71×10^{-6}	58.3%
	Router [10]	-0.138	51.3%	5.80×10^{-5}	1.07×10^{-4}	57.5%
	USAir [25, 26]	-0.208	42.1%	2.76×10^{-4}	3.70×10^{-4}	37.3%
Biological Network	PPI [27]	-0.102	50.5%	6.92×10^{-5}	1.02×10^{-4}	52.6%
	celegansneural [28, 29]	-0.163	56.7%	1.11×10^{-4}	3.21×10^{-4}	42.1%
	foodweb_Florida [26, 30]	-0.112	49.6%	1.90×10^{-4}	2.94×10^{-4}	34.4%
Social Network	SCN [11, 12]	0.161	61.4%	1.33×10^{-5}	1.07×10^{-5}	69.7%
	CA-HepTh [31]	0.268	63.1%	2.78×10^{-5}	1.96×10^{-5}	72.8%
	CA-GrOc [31]	0.659	80.6%	6.32×10^{-5}	2.78×10^{-5}	88.9%
Online Social Network	soc-Epinions1 [32]	-0.041	58.8%	5.81×10^{-7}	1.07×10^{-6}	71.6%
	Email-Enron [33, 34]	-0.111	58.9%	1.21×10^{-6}	3.19×10^{-6}	51.5%
Synthesized Network	ER [35]	-0.001	50.7%	1.24×10^{-5}	1.27×10^{-5}	50.4%

^a The result of ER network is an average over 10 times. We treat Soc-Epinions1, celegansneural and foodweb_Florida, originally directed networks, as undirected networks by treating each directed edge as an undirected one and eliminating duplicated edges.

TABLE II. Categorization of networks by global assortativity and edge assortativity statistics.

	$r > 0$	$r < 0$
$P(\rho_e > 0) > 50\%$	SCN CA-HepTh CA-GrOc	AS, Router soc-Epinions1 Email-Enron
$P(\rho_e > 0) < 50\%$	-	USAir foodweb_Florida

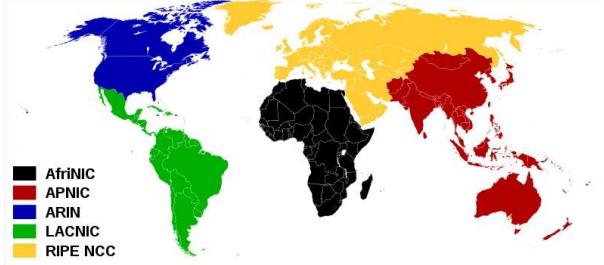


FIG. 2. (Color Online) Map of regional Internet registries.

States, Canada, several parts of the Caribbean region and Antarctica, APNIC for Asia, Australia, New Zealand, and neighboring countries, LACNIC for Latin America and parts of the Caribbean region, and RIPE NCC for Europe, the Middle East and Central Asia (see Fig. 2 for a graphical representation of the five RIRs' responsible regions). This gives us a coarse partition of the ASes according to the five regions. A more fine-grained partition is to further divide each region according to countries and regions. Hence, we have a two-level partitioning. The first-level groups consist ASes adhering to the same regional Internet registries, and the second-level groups consist ASes belonging to the same country and region, following the ISO 3166-1 standard.

Table. III reports both the intra-RIR and inter-RIR assortativity coefficients. We observe that except for ARIN, other RIRs all show assortativity internally. For inter-RIR connections, we observe that connections be-

tween ARIN and all other RIRs show dissortativity. RIPENCC exhibits similar phenomenon with ARIN except that its connections with AfrNIC exhibits some sort of assortativity. Connections among AfrNIC, APNIC, and LACNIC, all show assortativity. This connectivity tendency reflects the fact that broadly, the regions covered by ARIN and RIPENCC are the core of the Internet. However, RIPENCC differs from ARIN in the sense that RIPENCC itself is assortative whereas ARIN is dissortative. This could be more appropriately explained by the more fine-grained country and region connection tendencies. Fig. 3 reports the intra- and inter-country and region assortativity coefficients for those countries and regions whose observed ASN numbers are greater than 80 (we choose 80 as a threshold because we want to ensure that each RIR has at least one country or region in this map). In this figure, vacant grid means there is no observed AS connections between the two countries/regions. Different colors are used to discretize the strength of assortativity/dissortativity within and between countries/regions. Several clear patterns can be observed from this plot. Firstly, except for US, all other countries/regions are internally assortatively mixed, as illustrated by the diagonal of the plot. Secondly, there are a few countries/regions, namely, US, CA, GB, EU, DE, that primarily show dissortative connectivity tendencies to other countries/regions. Finally, inter-connections between other countries/regions are mostly assortative.

Statistically, on the RIR scale, we found that about 67.3% intra-RIR edges are assortative, whereas only 32.3% inter-RIR edges are assortative. And on the country/region scale, 69.7% intra-country/region edges are assortative, whereas only 44.9% inter-country/region edges are assortative. Considering the fact that globally an average of 60.4% edges are assortative, it is then apparent that on both scales, edges within the same regional area are more likely to be assortative than the average ratio 60.4%, whereas, edges linking different regional areas are far less likely to be assortative than the average ratio. This locality-driven difference in connec-

TABLE III. Intra-RIR and inter-RIR assortativity coefficients.

size		AfriNIC	APNIC	LACNIC	RIPENCC	ARIN
380	AfriNIC	9.35×10^{-4}	3.86×10^{-5}	1.13×10^{-5}	1.24×10^{-4}	-0.002
3711	APNIC	3.86×10^{-5}	0.014	1.48×10^{-4}	-2.93×10^{-4}	-0.01
1209	LACNIC	1.13×10^{-5}	1.48×10^{-4}	0.004	-4.61×10^{-4}	-0.007
13401	RIPENCC	1.24×10^{-4}	-2.93×10^{-4}	-4.61×10^{-4}	0.021	-0.083
11172	ARIN	-0.002	-0.01	-0.007	-0.083	-0.121

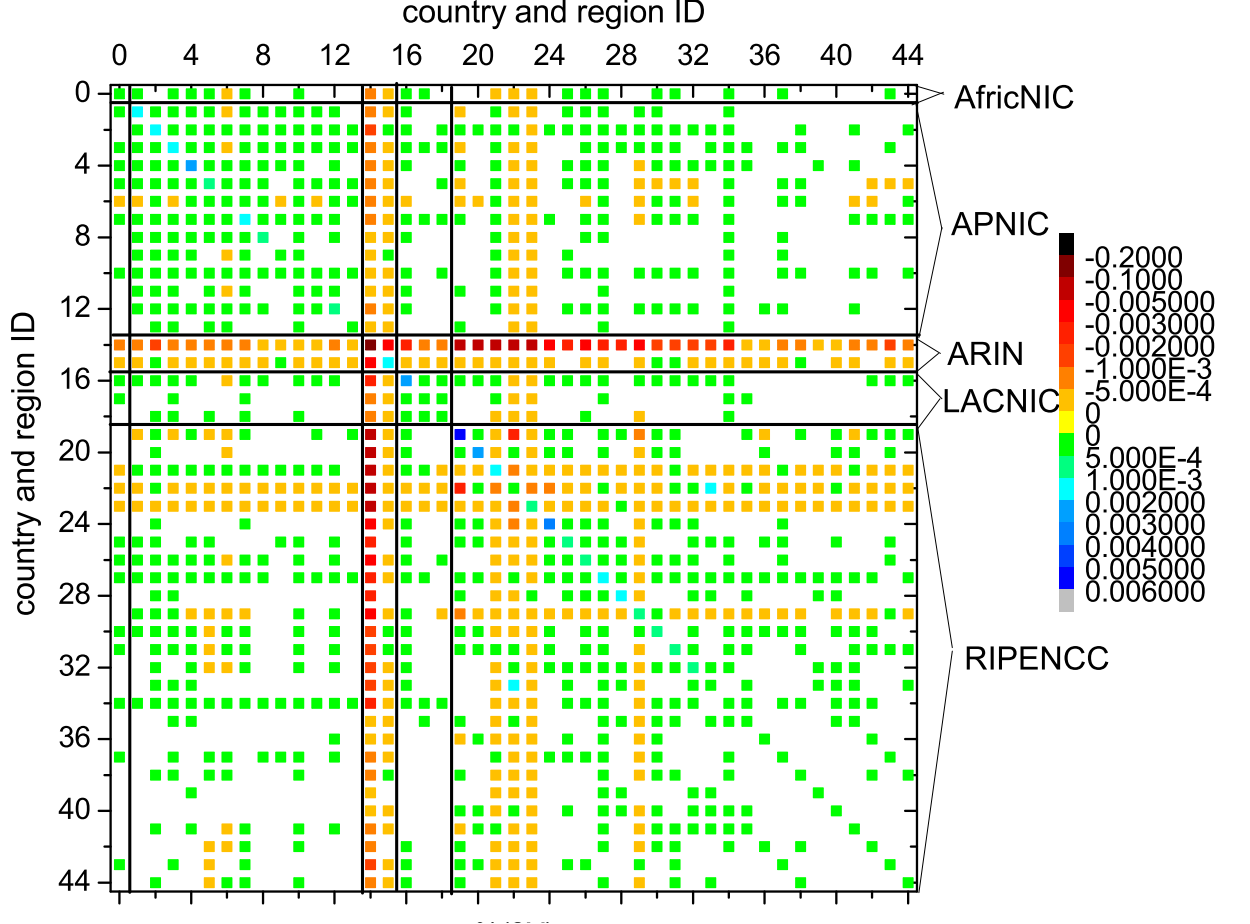


FIG. 3. (Color online) Connection tendencies between and within different countries and regions.

tivity patterns is a characteristic feature of AS-level Internet topology, which however, cannot be revealed by the global assortativity coefficient.

IV. DISCUSSION AND CONCLUSION

Prior to our definition, local assortativity coefficient is proposed as a local metric [37, 38] that measures the individual node's connection tendency, which is defined by calculating the contribution of each node to the global assortativity coefficient. However, the calculation is arguable because there is no precise and unique way to deterministically quantify each node v 's contribution to a

combined term U_q^2 collectively calculated from the edge set. For example, supposing the remaining degree of a node v is j , there may be many forms of the contribution of v , such as $(j/\sum_{v \in V} j) * U_q^2$, $(j^2/\sum_{v \in V} j^2) * U_q^2$ and so on. None of these forms can justify itself. This is because calculation of U_q^2 is a unified process, which is closely related to the complex correlation of the network structure, so we could not decompose this term into each node's contribution as if nodes were independent of each other. In contrast, our definition is more straightforward in that it calculates each edge's contribution to the global assortativity coefficient, rather than each node's contribution to a term in the formula. As a result, our definition completely avoids the bias issue in that definition [38]. More

TABLE IV. Country and region codes for corresponding IDs in Fig. 3, and the number of ASes owned by these countries and regions.

RIR name	ID	country and region code	number of ASes
AfriNIC	0	ZA	95
APNIC	1	AU	586
	2	KR	539
	3	JP	483
	4	ID	339
	5	IN	306
	6	HK	194
	7	CN	166
	8	TH	162
	9	NZ	151
	10	SG	123
	11	PH	118
	12	TW	100
	13	BD	85
ARIN	14	US	10406
	15	CA	674
LACNIC	16	BR	574
	17	AR	141
	18	MX	133
RIPENCC	19	RU	2544
	20	UA	1146
	21	GB	1059
	22	EU	1016
	23	DE	904
	24	PL	882
	25	CZ	505
	26	FR	431
	27	IT	423
	28	BG	349
	29	NL	348
	30	CH	324
	31	SE	306
	32	AT	268
	33	RO	243
	34	ES	213
	35	TR	170
	36	LV	150
	37	IL	149
	38	DK	141
	39	SI	125
	40	HU	123
	41	IR	117
	42	FI	111
	43	BE	110
	44	NO	105

importantly, from the edge assortativity, we can define the universal assortativity coefficient capable of network analysis.

To summarize, we present a universal assortativity coefficient (UAC) which can be used to calculate connection tendencies on any part of a network, such as communities, groups in multiple network scales. Indeed, given that the target edge set is set to all edges, UAC is exactly the global assortativity coefficient (GAC). In this sense, GAC is a special case of UAC. Moreover, this definition is deterministic, completely avoiding the bias issue accompanied with the node-based local assortativity coefficient definition. UAC helps to uncover individual, partial, and global assortativity patterns in various networks. Applying UAC to real world networks, we find that contrary to the popular expectation, most globally dissortative networks are still dominated by assortative edges, though with weak strength. This observation also motivates us to classify networks along two dimensions into four categories, characterized by their global assortativity coefficient and local assortativity statistics. It is expected that this measure can be widely applied to various networks such as popular online social networks, ubiquitous modern communication networks and transportation networks, help people uncover more hidden patterns in networks, and finally allow deep understanding of network dynamics caused by the structural difference discerned by the UAC.

V. ACKNOWLEDGEMENT

The authors thank Dr. Wenxu Wang for his valuable comments on this paper. This work is partly supported by the National Natural Science Foundation of China under Grant No. 61100178 and 61174152.

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